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Assess Knowledge of Healthcare Technologies and informatics enabled by Artificial Intelligence

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Abstract

Background: Healthcare is anticipated to increasingly incorporate artificial intelligence (AI) technologies into patient care. Recognizing public perceptions of these tools is crucial to their effective development and adoption. This exploratory study assessed participants' openness, concerns, and perceived advantages of AI-driven healthcare technologies and informatics, alongside socio-demographic, health-related, and psychosocial factors influencing these views.

Methods: A measurement tool was developed to represent six AI-based technologies that diagnose, predict, or suggest treatment options. This tool was deployed via an online survey completed by adults (N=936). Participants rated their openness toward each AI technology in healthcare contexts, as well as concerns and perceived benefits associated with each. Additionally, socio-demographic data, health status, and psychosocial factors such as trust in the healthcare system and technology were collected. Exploratory and confirmatory factors analyses of concern and benefit items revealed two main factors: overall levels of concern and perceived benefit. Descriptive statistics captured levels of openness, concern, and perceived benefit, while correlational analyses examined relationships between socio-demographic, health, and psychosocial variables and these perceptions. Concurrent associations were assessed using multivariable regression models.

Results: Participants expressed moderate openness to AI-driven healthcare technologies and informatics (M=3.1/5.0 ±0.9), with varying degrees of acceptance depending on the type of AI application. Statements of concern and benefit significantly influenced participants' views. Trust in healthcare systems and technology consistently emerged as strong correlates of openness, concern, and perceived benefits. Although other socio-demographic, health-related, and psychosocial factors showed weaker or negligible associations, multivariable models identified modest links between perceptions and variables like personality traits (e.g., conscientiousness, agreeableness), employment status, age, sex, and race.

Conclusions: Participants' openness to AI in healthcare appears tentative, implying that early engagement and exposure to AI technologies could substantially shape attitudes, especially as these technologies either reinforce or erode trust. Given the exploratory findings, further research is needed to clarify these relationships.

Keywords: *employment, Healthcare, technologies, socio-demographic, exploratory*

Introduction

Recent advancements in machine learning have sparked widespread enthusiasm about the potential for artificial intelligence (AI) to revolutionize healthcare delivery [1-6]. Rajkomar, Dean, and Kohane emphasize that the collective wisdom embedded in clinicians' decisions and the health outcomes of millions of patients should shape care for each individual, machine learning transcends being a mere tool—it is an essential technology for processing data beyond human cognitive capacity [2] .

However, alongside this enthusiasm come concerns about achieving these ambitious goals and the potential for unintended consequences [7-15]. Israni and Verghese have remarked, "The promise of AI is undeniable…the surrounding hype and fear exceed even that which followed the discovery of DNA's structure or the entire genome sequence." [7]

AI technologies are already reshaping healthcare practice, with applications for screening conditions like skin cancer, oral cancer, and tuberculosis, suggesting that these tools may broaden access to life-changing diagnostic resources [16-18]. The FDA has approved several AI-powered devices, including those for detecting wrist fractures and diabetic retinopathy [19, 20]. However, successful implementation of these technologies requires understanding and addressing patients' perspectives, as they are essential in sharing health data and engaging with AI tools [21-24]. Current research, though limited, shows that while patients see both benefits and risks in AI applications, they have varying levels of willingness to adopt these technologies.

A study in France, for instance, examined the views of 1,183 patients with chronic illnesses on biometric monitoring devices (BMDs) integrated into healthcare. Just 20% saw significant benefits, such as improved access and reduced treatment burden, outweighing risks like AI replacing human input or mismanaging private data. While 65% were open to using BMDs if controlled by humans, only 3% supported fully automated use; 22% opposed specific technologies, and 13% were unwilling to use any [25].

A PricewaterhouseCoopers study of 12,000 individuals from Europe, the Middle East, and Africa found that 54% of participants were open to AI and robotic technologies, while 38% were reluctant, and 7% were indifferent [26]. Participants' willingness varied with purpose; for instance, 37% were comfortable with AI monitoring a heart condition, while only 1% accepted AI for childbirth assistance. Another study in Australia reported 96% patient satisfaction with AI-based diabetic retinopathy screening, largely due to the convenience of automated assessments [27].

In U.S. interviews with dermatology patients, participants valued AI's potential for faster diagnoses, better access to care, and greater accuracy but noted risks of inaccurate diagnosis as a major drawback, with 94% preferring AI complemented by human oversight [28]. Similarly, a Dutch study found that limited AI knowledge might necessitate patient education to foster AI acceptance and enable informed contributions to its implementation. Patients expressed concerns about efficiency, accountability, reliability, and defining AI's role alongside human providers [29].

However, no study to date has explored levels of openness or the perceived concerns and benefits of AI in healthcare among U.S. adults, nor has it examined factors that might inform these perceptions. Context and task specifics of AI applications likely influence perceptions, as patients may respond differently to AI used for diagnosing versus treating serious or complex conditions like cancer versus a minor fracture [30, 31]. Likewise, AI-enabled technologies for home use, such as health apps and wearables, might be more appealing than those replacing human care in clinical settings. How tools function—whether to promote wellness or treat conditions—could also shape individuals' views.

Perceptions of AI in healthcare may also hinge on perceived risks and benefits. While enhanced decision-making efficiency and accuracy may be appealing, concerns about reduced professional discretion and personalized care remain [30, 32]. Broader societal concerns about AI's potential to impact fairness and worsen disparities are also relevant to healthcare. The National Academy of Medicine has highlighted that equity and inclusion should guide AI design and scaling, given that other consumer-facing technologies have sometimes intensified existing inequities [33]. Thus, people may have social justice concerns as AI tools become integrated into healthcare.

This exploratory study was conducted on which offers a geographically diverse sample more representative than local surveys but typically skewed toward younger, tech-savvy adults . Therefore, this study reflects perspectives that may not fully represent the population, and our findings are interpreted with this exploratory context in mind [37].

Methods

We developed the "Perceptions of AI Technologies in Healthcare" scale to assess people's openness, perceived risks, and perceived benefits of AI in healthcare. This tool used realistic, scenario-based examples to help participants understand AI applications within the healthcare context. The development team included physicians, social scientists specializing in bioethics and psychometrics, and a healthcare social worker. To minimize misconceptions, the term "artificial intelligence" was avoided throughout, using terms like "technology" and "computer programs" to focus on specific functionalities rather than generalized views of AI. The development process involved informant interviews, a literature review, drafting and revising items, and an initial factor analysis based on preliminary data.

The measure presented a range of AI-based healthcare applications in scenarios with varying emotional stakes (e.g., a minor injury versus cancer diagnosis), purposes (diagnosis, treatment, or prognosis), and settings (hospital, clinic, or home). An example scenario presented is as follows:

"You have been diagnosed with colon cancer. The clinic uses a computer program that analyzes data from thousands of colon cancer patients to estimate survival rates. Based on your medical profile, the program predicts you have a very low chance of surviving beyond six months."

Participants rated their openness to each technology on a 5-point Likert scale, from "not at all open" (1) to "extremely open" (5), with openness defined as a willingness to consider the use of the technology in their care. Each scenario then included items to evaluate nine specific ethical and practical concerns and benefits associated with AI in healthcare.

We identified these concerns and benefits through informant interviews and a literature review. Interviews with seven experts in bioinformatics, law, bioethics, and medicine explored their definitions of AI, how they explain it to laypeople, examples of current and future AI uses in healthcare, and likely concerns and benefits from a patient's perspective. We organized themes from these interviews and reviewed them against issues highlighted in the literature on AI in healthcare, encompassing more than 300 sources, including review articles discussing key ethical aspects [12,13,14,15, 38,39,40,41]. This process resulted in nine distinct dimensions—five concerns and four benefits—related to AI in healthcare.

Where an aspect could be perceived as either a concern or a benefit (e.g., accuracy), we categorized it based on literature and interview insights about what would be most salient to individuals. We wrote items covering each dimension to capture the full spectrum of potential concerns and benefits, anticipating factor analysis would further refine these into fewer dimensions.

For each scenario, participants responded to statements representing these concerns and benefits, using a 7-point Likert scale from "much more negative" (1) to "much more positive" (7) to indicate how each statement influenced their perception of the technology. The initial measure comprised 54 items—at least five per concern/benefit—to allow for the removal of items if necessary during factor analysis.

Two bioinformatics experts reviewed the initial measure to assess the technical feasibility and realism of the scenarios. Additionally, we conducted cognitive interviews with five diverse community members (in terms of age, race/ethnicity, and education) to ensure clarity [63].

Study Design and Data Collection Procedure

The Perceptions of AI Technologies in Healthcare measure, along with several validated additional measures, was administered through the Qualtrics platform. Participants were recruited on social media, a platform that connects individuals with tasks like surveys, with eligibility criteria 18 or older, having completed 100 prior tasks, and maintaining a 98% approval rating. The survey was presented as a study on healthcare technologies and informatics , with a 3.65 SAR compensation for the 30-minute completion time, set to meet minimum wage for the task duration. MTurk has been shown to produce data as reliable as lab-based studies [35, 64].

Data collection occurred in two stages: an exploratory factor analysis (EFA) for initial concern and benefit item analysis, followed by a confirmatory factor analysis (CFA) to validate the EFA findings. Assuming six factors and retaining at least five items per factor, a sample size of 400 was deemed appropriate for reliable results [65, 66]. We aimed for 400 participants for both the EFA and CFA, ensuring sufficient sample size for further analyses.

This study collected comprehensive data from participants at a single point in time. While common source bias is a potential concern in single-instrument survey studies, the choice of a survey was appropriate given the objective of assessing individual perceptions. The survey was designed thoughtfully to minimize bias [67, 68]. The openness, concern, and benefit variables were measured using a scenario-based task with unique scales and anchors, while trust and personality were assessed with established psychosocial questionnaires.

Perceptions of AI Technologies in Healthcare

Primary outcome variables included openness to AI in healthcare, perceived concerns, and perceived benefits. We measured these using a scenario-based instrument, which randomized the presentation of scenarios and items to control for order effects. A factor analysis informed the refinement of the concern and benefit items, ultimately retaining 22 concern and 16 benefit items. Scores for each construct were calculated by averaging item responses, resulting in possible scores between 1 and 7 for concern and benefit, and between 1 and 5 for openness.

Ten Item Personality Inventory (TIPI)

The TIPI measures five personality traits—openness, conscientiousness, extraversion, agreeableness, and emotional stability [64]. Participants rated ten paired traits on a 7-point scale (1 = “strongly disagree” to 7 = “strongly agree”), producing five trait scores by averaging two items each. This brief personality measure was included to explore how personality, particularly openness, might relate to openness to AI in healthcare, as personality traits like conscientiousness are often linked with health-promoting behaviors [69].

Trust in Health Information Systems

Trust in health systems and health information sharing was assessed with four subscales: fidelity, competency, trust, and integrity [70]. An example item is, “The organizations that have my health information and share it would try to hide a serious mistake.” Items were scored on a 4-point Likert scale (1 = “not at all true” to 4 = “very true”), and an overall health system trust score was calculated by summing the subscale means, yielding a possible range of 4 to 16. We expected higher trust in health systems to correlate with openness to AI and a greater perceived benefit, and to negatively correlate with concerns.

Faith in and Trust of General Technology

A brief scale assessed faith in and trust of general technology [71], with items such as, “I think most technologies enable me to do what I need to do.” Responses were recorded on a 7-point Likert scale (1 = “strongly disagree” to 7 = “strongly agree”), and mean scores were calculated. We hypothesized that greater trust in technology would positively correlate with perceived benefits and openness and inversely correlate with concerns.

Social and Economic Conservatism Scale

This scale assessed social and economic conservatism, asking participants to rate 12 concepts (e.g., business, traditional values) on a sliding scale from 0 to 100. Social and economic conservatism scores were the mean ratings for relevant concepts. We included this scale to investigate whether conservatism might relate to lower openness and heightened concerns about changes in healthcare.

Health Status and Healthcare Access

We collected data on self-reported health status, healthcare satisfaction, primary insurance type, healthcare location, and choice availability [73]. This information was expected to relate to perceptions of AI technologies in healthcare.

Socio-demographics

We gathered data on age, sex, employment, income, ethnicity, race, education level, and community type.

Statistical Analysis

A confirmatory factor analysis (CFA) on the round two sample validated this factor structure. We assessed internal consistency with Cronbach's alpha for retained concern, benefit, and openness items. Descriptive statistics summarized participant characteristics. Given no significant differences across the two data collection rounds, we combined the samples for further analyses.

We used descriptive statistics to explore overall openness, concern, and benefit perceptions regarding AI technologies in healthcare. Bivariate correlations examined the associations between socio-demographic, health, and psychosocial variables and levels of openness, concern, and benefit. Additionally, three stepwise linear regressions (with openness, concern, and benefit as outcomes) were conducted to identify predictors. Age, sex, race, and ethnicity were controlled in the first step of each model. Other socio-demographic, health, and psychosocial variables were entered as potential predictors based on R^2 criteria (probability-of-F-to-enter ≤ 0.05, probability-of-F-to-remove ≥ 0.10). Healthcare satisfaction was excluded, as it was only collected from participants with recent healthcare use, which would significantly reduce the sample size.

Results

Participant Overview

This study involved 936 individuals, primarily White, college-educated, and generally healthy, with an average age in the mid-thirties. Table 1 outlines their demographics and healthcare-related characteristics.

Factor Analysis of AI Concern and Benefit Items

In an exploratory factor analysis (EFA) using the first sample, two key factors emerged: one representing participants' concerns (22 items) and another for perceived benefits (16 items), accounting for 22% and 18% of variance, respectively. Sixteen items were omitted as they did not align with these factors or were redundant. A confirmatory factor analysis (CFA) with the second sample validated this structure, achieving an acceptable model fit.

Participants were most open to AI applications in heart attack risk monitoring ($M = 3.40$, $SD = 1.20$), followed by cancer survival prediction ($M = 3.37$, $SD = 1.16$), ankle fracture diagnosis ($M = 3.22$, $SD = 1.20$), and anxiety medication selection ($M = 3.14$, $SD = 1.16$). Openness was lowest for mental health apps ($M = 2.77$, $SD = 1.29$) and a video-based facial expression monitoring system for post-surgery pain ($M = 2.41$, $SD = 1.35$). All scenario comparisons were statistically significant ($p < 0.01$). Table 2 presents descriptive statistics for openness, concern, and benefit scores alongside psychosocial measures, with moderate overall openness and varied responses to concerns and benefits.

Correlational Analysis

Table 3 outlines the correlations between socio-demographic, health, and psychosocial factors and openness, concern, and benefit scores. Age and sex modestly influenced openness, with younger participants and males being more open to AI. Females tended to express greater concerns. Full-time employment was linked to both higher openness and lower concern. Greater healthcare access and satisfaction correlated with perceived benefits, while poorer health status correlated with greater concern.

Notably, trait-based personality openness showed a weak association with openness to AI ($r = 0.07$), indicating specific attitudes toward AI beyond general openness. Agreeableness and conscientiousness were associated with perceived benefits, and social conservatism correlated slightly with lower concern. The strongest associations with openness, concern, and benefit ratings were observed for trust in health and technology, with these correlations surpassing those of other variables by 1.5 to 4 times.

Regression Analysis

Table 4 presents regression analyses, highlighting key predictors of openness, concern, and benefit. In the openness model, trust and faith in technology significantly correlated with openness, while full-time employment and trust in health systems were moderate predictors. Older age, conscientiousness, and economic conservatism were linked to slightly lower openness, with this model explaining 26% of variance.

The concern model indicated that trust in health systems and technology was associated with reduced concern, whereas conscientiousness, agreeableness, and female gender were associated with greater concern. Lower concern correlated with higher extraversion and social conservatism, with the model explaining 21% of variance.

The benefit model showed that trust and faith in technology predicted perceived benefits. Race was modestly linked, with non-White participants perceiving more benefits. This model explained 25% of variance.

Table 1 Participant socio-demographics and healthcare variables

	Sample 1 (N = 469)	Sample 2 (N = 467)	Total (N = 936)	
Age in years	M = 37.2 ± 11.0 Range 65, 18–83	M = 36.9 ± 11.0 Range 53, 19–72	M = 37.1 ± 11.0 Range 65, 18–83	
		n (%)	n (%)	n (%)
Sex (male)[a]		256 (55)	258 (55)	514 (55)
Race/ethnicity[b,c]				
White		383 (82)	398 (85)	781 (83)
Highest education				
Less than high school or other		6 (1)	2 (< 1)	8 (1)
High school graduate		57 (12)	63 (14)	120 (13)
Some college		100 (21)	112 (24)	212 (23)
Associate’s degree		48 (10)	63 (14)	111 (12)
Bachelor’s degree		205 (44)	181 (39)	386 (41)
Graduate degree		53 (11)	46 (10)	99 (11)
Employment status				
Employed full-time		329 (70)	308 (66)	637 (68)
Employed part-time (not full-time student)		28 (6)	30 (6)	58 (6)
Full-time student		11 (2)	11 (2)	22 (2)
Self-employed		47 (10)	64 (14)	111 (12)
Unemployed		22 (5)	23 (5)	45 (5)
Other[e]		32 (7)	31 (7)	63 (7)

Annual household income[f]			
< 10,000 SAR	75 (16)	57 (12)	132 (14)
10,001–15,000 SAR	118 (25)	148 (32)	266 (28)
15,001–20,000 SAR	139 (30)	134 (29)	273 (29)
20,001–30,000 SAR	87 (19)	81 (17)	168 (18)
> 30,001 SAR	46 (10)	40 (9)	86 (9)
Type of community			
Urban	139 (30)	126 (27)	265 (28)
Suburban	242 (52)	242 (52)	484 (52)
Rural	88 (19)	99 (21)	187 (20)
Health status			
Excellent	83 (18)	69 (15)	152 (16)
Very good	154 (33)	174 (37)	328 (35)
Good	155 (33)	139 (30)	294 (31)
Fair	57 (12)	70 (15)	127 (14)
Poor	20 (4)	15 (3)	35 (4)
Primary health insurance type			
Private	294 (63)	258 (55)	552 (59)
Medicare	39 (8)	48 (10)	87 (9)
Medicaid	52 (11)	62 (13)	114 (12)
Medicare advantage	11 (2)	14 (3)	25 (3)
No health insurance	73 (16)	85 (18)	158 (17)
Typical healthcare service location			
Doctor’s office or private clinic	324 (69)	291 (62)	615 (66)
Urgent care center	59 (13)	74 (16)	133 (14)
Community health center or other public health clinic	25 (5)	37 (8)	62 (7)
No regular place of care	32 (7)	48 (10)	80 (9)
Hospital emergency room	18 (4)	8 (2)	26 (3)
Other	11 (2)	9 (2)	20 (2)
Medical care choice[g]			
A great deal of choice	123 (26)	99 (21)	222 (24)
Some choice	236 (50)	237 (51)	473 (51)
Very little choice	83 (18)	100 (21)	183 (20)

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No choice	22 (5)	19 (4)	41 (4)
Healthcare satisfaction[h]			
Very satisfied	157 (34)	132 (28)	289 (31)
Somewhat satisfied	171 (37)	196 (42)	367 (39)
Somewhat dissatisfied	38 (8)	26 (6)	64 (7)
Very dissatisfied	7 (2)	8 (2)	15 (2)

1. Some percentages add to more than 100%, due to rounding
2. [a]n = 11 selected other or prefer not to answer
3. [b]not mutually exclusive categories, participants selected all that apply
4. [c]n = 8 selected prefer not to answer
5. [d]American Indian, Alaska Native, Native Hawaiian, or Pacific Islander
6. [e]caregiver or homemaker, retired, or other
7. [f]n = 11 selected prefer not to answer
8. [g]n = 17 selected "I don't know"
9. [h]only asked of those indicating healthcare utilization in last 12 months (n = 735)

Table 2 Descriptives for openness, concern, and benefit scores and psychosocial variables

	No. of items	**Cronbach's α**	**Min**	**Max**	**Mean**	**SD**	**95% CI for mean**
Openness[a]	6	.80	1.0	5.0	3.06	.87	[3.00, 3.12]
Concern	22	.92	1.2	7.0	5.34	.82	[5.29, 5.39]
Benefit	16	.89	2.6	7.0	5.49	.75	[5.44, 5.54]
Health System Trust Index	20	.91	4.0	16.0	9.48	2.63	[9.31, 9.65]
Trust in technology	3	.89	1.0	7.0	4.95	1.32	[4.87, 5.03]
Faith in technology	4	.87	1.0	7.0	5.56	.83	[5.51, 5.61]
Conscientiousness	2	.67	1.5	7.0	5.59	1.23	[5.51, 5.67]
Agreeableness	2	.55	1.0	7.0	5.37	1.30	[5.29, 5.45]
Extraversion	2	.80	1.0	7.0	3.37	1.77	[3.26, 3.48]
Emotional stability	2	.82	1.0	7.0	4.91	1.64	[4.80, 5.02]
Openness (trait-based)	2	.61	1.0	7.0	5.08	1.34	[4.99, 5.17]
Social conservatism	7	.90	0.0	100.0	55.77	25.65	[54.13, 57.40]
Economic conservatism	5	.73	0.0	100.0	53.63	20.53	[52.31, 54.95]

1. N = 936, except for agreeableness (n = 935), emotional stability (n = 934), faith in technology (n = 934), trust in technology (n = 933) due to missing data

2. [a]Correlations between the Perspective of AI Technologies scores: Openness with concern, r = − .52, 95% CI [− .57, − .47]; openness with benefit, r = .61, 95% CI [.57, .65]; concern with benefit, r = − .05 CI [− .11, − .01]

Table 3 Correlations of openness, concern, and benefit scores with all study variables

	Openness		Concern		Benefit	
	r	95% CI	r	95% CI	r	95% CI
Socio-demographics						
Age	− .12	[− .18, − .06]	.06	[.00, .12]	− .03	[− .09, .03]
Sex (1 = Male, 0 = Female)	.10	[.04, .16]	− .20	[− .26, − .14]	− .03	[− .09, .04]
Race (1 = White, 0 = Non-White)[a]	− .05	[− .11, .01]	.01	[− .05, .07]	− .08	[− .14, − .02]
Ethnicity (1 = Latino, 0 = non-Latino)	.06	[.00, .12]	− .09	[− .15, − .03]	− .02	[− .08, .04]
Household income	.07	[.01, .13]	− .08	[− .14, − .02]	.07	[.01, .13]
Community type	.06	[.00, .12]	− .06	[− .12, .00]	.01	[− .05, .07]
Employment status[b]	.17	[.11, .23]	− .18	[− .24, − .12]	.05	[− .01, .11]
Education	.04	[− .02, .10]	.03	[− .03, .09]	.01	[− .05, .07]
Health status and access						
Health status	.08	[.02, .14]	− .12	[− .18, − .06]	− .02	[− .08, .04]
Healthcare location[c]	.03	[− .03, .09]	− .01	[− .07, .05]	.02	[− .04, .08]
Healthcare choice[d]	.08	[.02, .14]	− .06	[− .12, .00]	.11	[.05, 17]
Health insurance (1 = Yes, 0 = No)	.09	[.03, .15]	− .10	[− .16, − .04]	.05	[− .01, .11]
Healthcare satisfaction (n = 735)	.11	[.04, .18]	− .07	[− .14, .00]	.14	[.07, .21]
Psychosocial variables						
Health System Trust Index	.27	[.21, .33]	− .27	[− .33, − .21]	.21	[.15, .27]
Trust in technology	.41	[.36, 46]	− .21	[− .27, − .15]	.41	[.36, .46]
Faith in technology	.38	[.32, .43]	− .10	[− .16, − .04]	.46	[.41, .51]
Conscientiousness	.02	[− .04, .08]	.11	[.05, .17]	.15	[.09, .21]
Agreeableness	.08	[.02, .14]	.11	[.05, .17]	.20	[.14, .26]
Extraversion	.08	[.02, .14]	− .12	[− .18, − .06]	.04	[− .02, .10]
Emotional stability	.08	[.02, .14]	− .06	[− .12, .00]	.07	[.01, .13]
Openness (trait-based)	.07	[.01, .13]	.07	[.01, .13]	.05	[− .01, .11]
Social conservatism	− .01	[− .07, .05]	− .10	[− .16, − .04]	.05	[− .01, .11]
Economic conservatism	− .06	[− .12, .00]	− .06	[− .12, .00]	.02	[− .04, .08]

1. N = 936 (except as noted for specific variables in Tables 1 and 2)
2. [a]Participants who selected any race other than White, or in addition to White, were classified as Non-White for purposes of this analysis

3. [b]1 = full-time employment, 0 = all other options
4. [c]1 = doctor office or private clinic, 0 = all other options
5. [d]1 = great or some choice; 0 = little to no choice

Table 4 Stepwise regression models predicting openness, concern, and benefit

Predictor	Model 1: Openness			Model 2: Concern			Model 3: Benefit		
	B	95% CI	β	B	95% CI	β	B	95% CI	β
Age	−0.01	[−0.01, 0.00]	−0.07*	0.00	[0.00, 0.00]	0.00	0.00	[−0.01, 0.00]	−0.03
Sex	0.08	[−0.02, 0.18]	0.05	−0.22	[−0.32, −0.12]	−0.13***	−0.07	[−0.15, 0.02]	−0.04
Race	−0.01	[−0.14, 0.11]	−0.01	−0.00	[−0.12, 0.12]	−0.00	−0.12	[−0.22, −0.01]	−0.06*
Ethnicity	0.05	[−0.14, 0.23]	0.01	−0.15	[−0.33, 0.03]	−0.05	−0.11	[−0.26, 0.05]	−0.04
Employment status	0.27	[0.16, 0.37]	0.14***	−0.24	[−0.35, −0.13]	−0.14***			
Health status				−0.23	[−0.36, −0.09]	−0.11**			
Health system trust	0.04	[0.02, 0.06]	0.12***	−0.06	[−0.08, −0.04]	−0.20***			
Trust in technology	0.17	[0.12, 0.21]	0.25***	−0.10	[−0.14, −0.06]	−0.16***	0.12	[0.08, 0.16]	0.22***
Faith in technology	0.22	[0.15, 0.29]	0.21***				0.30	[0.24, 0.37]	0.34***
Conscientiousness	−0.06	[−0.10, −0.02]	−0.09**	0.12	[0.08, 0.16]	0.18***			
Agreeableness				0.10	[0.06, 0.14]	0.15***			
Extraversion				−0.04	[−0.07, −0.01]	−0.08**			
Social conservatism				0.00	[0.00, 0.00]	−0.07*			

Economic conservatism	0.00	[− 0.01, 0.00]	− 0.07*						
R^2	.26***			.21***			.25***		

1. N = 916. Age, sex, race, and ethnicity entered in a first step as control variables. Age is continuous. Variables are coded as follows: Sex (1 male; 0 female), race (1 White; 0 non-White), and ethnicity (1 Latino; 0 not-Latino). Employment status (1 full-time; 0 other); health status (1 good/very good/excellent; 0 poor/fair)
2. *p < .05; **p < .01; ***p < .001

Discussion

This study focused on perceptions of AI-driven healthcare technologies and informatics through a scenario-based assessment of openness, concern, and perceived benefit. We evaluated overall openness across six different applications of AI in healthcare, where concern items addressed issues like privacy loss, lack of transparency, reduced clinician involvement, rising costs, and inequitable benefits across demographics (e.g., gender or racial groups). In contrast, benefit items emphasized aspects such as improved access and convenience, enhanced care quality, lowered healthcare costs, and increased personal health knowledge. Additionally, we measured various socio-demographic, health-related, and psychosocial variables to identify factors influencing openness, concern, and perceived benefit. Data collection was conducted, a crowdsourcing platform that provides cost-effective access to a diverse participant pool, though the interpretation of our findings should consider the characteristics of our sample.

Our sample was entirely composed of residents, which may limit the generalizability of the results to other countries, as we aimed to study perceptions among individuals within a common national health system. The sample included relatively young, healthy, and predominantly White adults, which does not reflect all subpopulations , with over 900 participants, we identified significant variations in age, self-reported health status, and race, revealing some associations with perceptions of AI-enabled healthcare technologies and informatics . These associations persisted even after controlling for variables such as trust in healthcare. Notably, older individuals exhibited less openness than younger participants; males expressed lower concern than females; and being employed full-time correlated with greater openness and reduced concern. Participants in good to excellent health reported lower levels of concern, indicating a need to explore perceptions among individuals with poorer health status. These findings suggest further investigation into socio-demographic and health-related variables affecting acceptance of AI technologies is necessary.

Overall, participants demonstrated moderate openness towards these technologies, although opinions varied by application. The two technologies that predicted serious diseases—the risk of heart attack and likelihood of cancer survival—garnered the highest ratings. Openness towards these AI applications may stem from familiarity, given the high prevalence of these diseases and the frequent exposure Americans have to preventive information regarding them [74]. Conversely, participants were least receptive to a device predicting post-surgery pain and a mental health app. This lower openness might be related to concerns about invasiveness, a preference for human interaction, or stigma associated with pain management and mental health treatment.

Trust in the healthcare system, along with faith in technology, exhibited the strongest and most consistent relationships with openness to AI healthcare technologies and informatics and evaluations of their potential benefits and drawbacks. Consequently, strategies for developing and implementing AI in healthcare should prioritize building and maintaining trust. Additionally, exploring how interpersonal trust in individual healthcare providers influences attitudes towards AI technologies may be vital [75, 76]. The observed connection between trust and perceptions of AI in healthcare is particularly significant, especially as Americans have reported declining trust in the healthcare system and lower confidence in physicians in recent years [77].

Certain personality traits also emerged as predictors of perceptions. Specifically, conscientiousness and agreeableness influenced concern similarly to trust. Individuals high in conscientiousness tend to be responsible and goal-oriented, which correlates with better health and greater well-being [69]. Therefore, the concern items addressing privacy loss and transparency may be especially troubling for those with high conscientiousness. Agreeableness is associated with warmth and empathy [78], so the social justice-related items depicting unfairness and those illustrating loss of personal interaction with healthcare providers may provoke greater concern. Given that personality traits are generally stable in adulthood, addressing their influence on perceptions and acceptance of new AI healthcare technologies and informatics may pose challenges. Additionally, conservatism represents a relatively stable set of political and social beliefs; while only weakly associated with perceptions in this study, the potential influence of these beliefs warrants further examination.

It is noteworthy that participants exhibited a typical response pattern when confronted with potential concerns and perceived benefits of AI technologies in healthcare. Overall, a slight decrease in perceptions was noted when concerns were introduced, contrasted by a slight increase in favorability when benefits were presented. Benefits elicited a somewhat stronger positive response than concerns prompted negative perceptions, suggesting the importance of emphasizing the advantages of these technologies. However, the overall increase compared to the decrease was minimal, which may lack clinical significance. Future research should aim to untangle the perceived risks and benefits and explore which trade-offs, if any, participants are willing to accept in various healthcare contexts. A qualitative approach, allowing participants to provide open-ended responses to healthcare scenarios, may prove beneficial.

Additionally, we developed items reflecting different types of concerns and benefits to determine which issues elicited the most worry and enthusiasm. We anticipated participants would differentiate between distinct benefits and concerns (e.g., quality, privacy, and cost), and cognitive interviews indicated they could distinguish the various domains covered by the questions. However, factor analysis revealed two underlying response patterns representing a general level of concern and perceived benefit. It appears that participants reacted to the benefit/concern framing (i.e., positive/negative) rather than evaluating the specific underlying issues.

This may indicate that the positive/negative framing amplified the emotional impact of the statements, guiding responses through a general affective lens (e.g., “I like or dislike this”). Participants were predominantly young and likely digitally literate [36], which might have led to familiarity with similar benefits (e.g., convenience and quality) and concerns (e.g., cost and privacy) associated with other technologies, thereby diminishing the specificity of their responses. Conversely, this pattern of general versus specific responses may suggest that perceptions of these technologies remain somewhat fragile, potentially due to limited knowledge or experience with AI technologies in healthcare.

The manner in which these technologies are marketed to the public is likely to play a crucial role in fostering openness and positive perceptions. Initial experiences that patients have with AI-driven healthcare technologies and informatics are also expected to significantly shape their views. When encountering novel and unfamiliar technologies, patients will need to trust the recommendations generated by these tools and engage with the information presented by their healthcare providers [79]. In some instances, patients may need to use these new tools directly over time [80]. To maximize the potential benefits of AI tools in healthcare, it is essential to incorporate user and patient perspectives. Collaborative efforts involving technology developers, informaticians, social scientists, clinicians, and patient engagement experts will be best positioned for this task during both development and adoption phases [7, 81]. Implementation strategies should also be considered to enhance the adoption, integration, and sustainability of innovative technologies in clinical practice [82]. Furthermore, addressing the underrepresentation of specific populations in both data collection and uptake of new health technologies is crucial to mitigate the risk of exacerbating existing health disparities [22, 33, 50].

Conclusion

Despite limitations, this study presents a novel, scenario-based approach for assessing public views on AI in healthcare, which could be adapted for future research. Our findings indicate moderate openness among younger adults toward AI in healthcare, highlight the role of trust in fostering acceptance, and underscore the influence of socio-demographic and psychosocial factors on perceptions. These insights could guide further exploration of public views on AI innovations in healthcare.

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